

US EPA ARCHIVE DOCUMENT

Effects of Exposure Dynamics in Dose Response Relationships

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Towards a Physiologically-Based Dose – Response Model

• Rationale

- Low dose extrapolation
 - Empirical data only exists in high-doses
- Understanding dominant modes of transmission
 - Optimal intervention strategies depend on which modes transmission are dominant
 - E.g., face mask vs. decontamination for influenza control

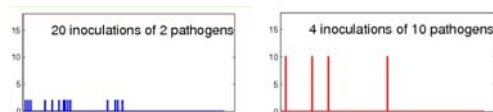
Dose Response: The Exponential Model

• Biological rationale

- Single hit model
 - Any pathogen has some probability of infection
 - Each pathogen acts independently
 - These assumptions lead us to the exponential model for risk

$$1 - e^{-rD}$$

- Risk depends on dose and r , the per pathogen risk
- Does risk depend on time between inoculations?



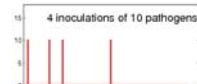
Biological Issues with Time- Independence

• Time independence

- Implies immune system plays no role in controlling infection
- Immune system operates at time-scales ranging from minutes to weeks
- Time-scale of environmental contamination to exposure can be minutes to hours
 - The innate immune system is active at this time scale

Physiologically-based Dose Response Behavior

$$F(\{d_{t_0+i\Delta t}\}_{i=0}^n)$$



Assumption 1:

Inoculations occur over short time period. Means doses can be summed

$$F(\{d_{t_0+i\Delta t}\}_{i=0}^n) = F(\sum_{i=0}^n d_{t_0+i\Delta t}) \text{ when } \Delta t \rightarrow 0$$

Assumption 2:

Inoculations occur over very long time period. Means risks from each inoculation are independent

$$F(\{d_{t_0+i\Delta t}\}_{i=0}^n) = 1 - \prod_{i=0}^n (1 - F(d_{t_0+i\Delta t})) \text{ when } \Delta t \rightarrow \infty$$

Assumption 3:

Inoculations occur over intermediate time periods. Means risk should decrease for longer exposure periods

$$F(\{d_{t_0+i\Delta t}\}_{i=0}^n) < F(\{d_{t_0+i\Delta t_j}\}_{i=0}^n) \text{ when } \Delta t_i > \Delta t_j$$

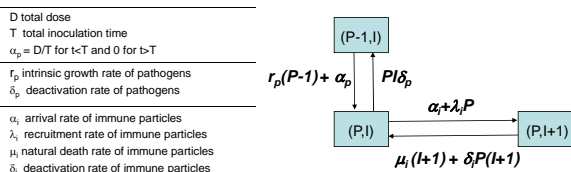
Cumulative Dose Model

- Continuous time Markov chain model can capture the needed dynamics
 - Dose has less probability of infection if the time of inoculation is longer
 - Time-dependent dose-response experiments are needed to inform the dynamics of this dose response relationship

System state variables and parameters

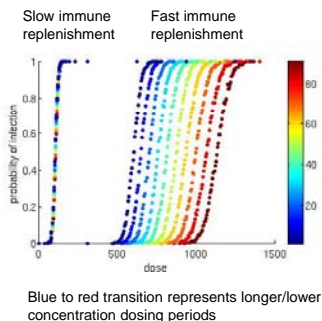
P # of pathogens
I # of immune particles

Model description



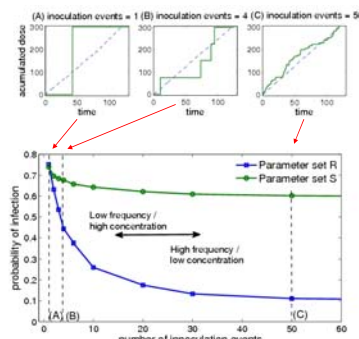
Cumulative Dose Model: Dynamics

- Slow immune replenishment ($\alpha=0.001$):
 - Dose-response function is independent of dosing time periods
- Fast immune replenishment ($\alpha=0.1$):
 - Shorter dosing regimes shifts dose-response function to left (increased infectivity)



Cumulative Dose Model: Effects of Number of Inoculations on Risk

- Three different inoculation events
 - Same total dose
- Have different risks



Conclusions

- Physiologically based dynamic dose-response models
 - Incorporate an important time dependent property of infection dynamics
 - The risk of one hundred pathogens at once is higher than the risk of one pathogen every day for one hundred days
- What impact do these dynamics have on transmission systems models and the design of interventions?
 - Integration to a transmission model is computationally infeasible
 - Need a simpler model

Simple Cumulative Dose Model

$$\frac{dD}{dt} = -\gamma D^\alpha$$

- D represents inoculated pathogens that are accumulated within the host
- Pathogen immune system interaction
 - Pathogens are removed due to the action of the immune system
 - The effectiveness of the immune system decreases as the number of pathogens increase
- α governs the time dependence between inoculations
 - $\alpha = 1$ is the time independent, exponential condition
 - $\alpha < 1$ is the time dependent condition
- Expect life-time of a pathogen is (n is the number of initial pathogens)

$$n^\alpha \gamma^{-1}$$

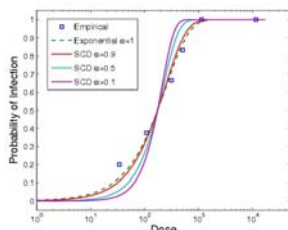
Simple Cumulative Dose Model: Single Inoculation

Single inoculation case.

$$P_{inf}(D) = 1 - e^{-\int_0^T D(t) dt}$$

Where

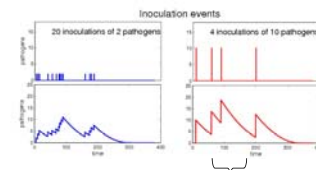
- T_p , the time to extinction of pathogens, is a function of the immune system (α, γ) and pathogen (r)
- s , the risk associated to a single pathogen that persists over time, is function of the immune system (α, γ) and pathogen (r)



Simple Cumulative Dose Model: Multiple Inoculation

Multiple inoculation case

$$P_{inf}(D) = 1 - e^{-\int_0^T D_n(t) dt}$$



The same total dose of pathogens inoculated in 4 events instead of in 20 events persist longer, and therefore, give a higher risk of infection

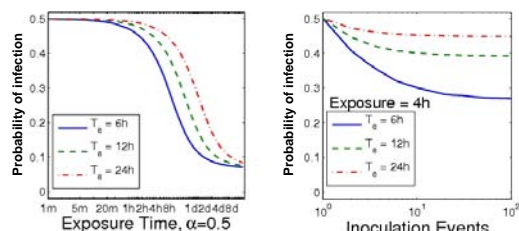
Total dose is the sum of each inoculation

Dose from each inoculation is a function of the prior dose

$$\int_0^\infty D_m(t) dt = \sum_{i=1}^{n-1} \left[\int_0^{t_i} D(t, D(t_i) + d_i) dt \right] + \int_0^\infty D(t, D(t_n) + d_n) dt$$

Simple Cumulative Dose Model: Qualitative Behavior

- This simple cumulative dose model exhibits similar behavior as the more complex pathogen-immune interaction model
 - Risk decreases as exposure time or inoculation events increase



Incorporating Dynamic Dose-Response Functionality in a Transmission Model

- The classical SIR model does not take into account environment

$$\frac{dS}{dt} = -\beta SI \quad \frac{dS}{dt} = -Sf(E)$$

$$\frac{dE}{dt} = g(I)$$

- To model environmental exposure a dose-response function, f , is required to determine infectivity

Incorporating Dynamic Dose-Response Functionality into a Transmission Model

- If immune system impacts the risk of infection
 - The probability of becoming infected is calculated as a function of the current level of pathogen within the host.
 - The number of pathogens in individual j residing in cell j evolves as a function of fomite pickup, C_{fj} , airborne pickup, C_{aj} , and die off within host

$$D_i \left\{ \begin{array}{l} + \text{pickup } C_{fj} \text{ at self-inoculation rate} \\ + \text{pickup } C_{aj} \text{ at breathing rate} \\ -1 \text{ at a rate } \gamma D_i^p \end{array} \right.$$

- The per capita force of infection at every dt is a function of pathogen infectivity, r , and immune system dynamics, α , γ
 - $f(E)$ from previous slide becomes

$$\hat{r}\gamma(2-\alpha)\left(\frac{\log(\frac{1}{\hat{r}})}{-\hat{r}}\right)^{\alpha-1} D_i dt$$

Incorporating Dynamic Dose-Response Functionality into a Transmission Model

- How do the dose response dynamics impact fomite vs. airborne transmission?
- Simulation scenario (assumptions)
 - Same $TCID_{50}$ for fomite and airborne
 - Contamination is constant
 - Same dose received via fomite and air
- These assumptions are all wrong, but allows us to compare the relative impacts of fomite and airborne routes of transmission

Risk	$\alpha=1$ $TCID_{50}=3.2$	$\alpha=0.5, T_s=12h$ $ID_{50}=64$	$\alpha=0.1, T_s=12h$ $ID_{50}=64$	$\alpha=0.1, T_s=12h$ $ID_{50}=640$	$\alpha=0.1, T_s=12h$ $ID_{50}=6400$
R_{total}	0.2	0.1	0.03	0.04	0.04
R_{fomite}	0.11	0.05	0.02	0.03	0.03
R_{air}	0.11	0.02	0.003	0.0005	0.0001
R_{fomite}/R_{air}	1.0	2.0	7.6	52	366

Conclusions

- Dynamic dose-response models can capture the immune system impact on infection
 - The crucial issue is the time course of exposure
 - The risk of exposure of one hundred pathogens at once is not same as the risk of exposure of one pathogen every day for one hundred days
- Implications
 - Risk of infections are more accurately captured
 - Immune system serves to attenuate the impact of low-level longer term exposure
 - Since temporal patterns of exposure differ by route of transmission, the dose response relationship can impact intervention strategies
 - Fomite exposure has fewer but higher magnitude inoculation events
 - Airborne exposure has more but lower magnitude inoculation events